Volume 3, No. 11, November 2012

Journal of Global Research in Computer Science

ISSN-2229-371X

RESEARCH PAPER

Available Online at www.jgrcs.info

BROADBAND INTERFERENCE SUPPRESSION USING VOLTERRA FILTERS

Sheena Agarwal[*1], R.C. Jain [2], D.B. Ojha[3]

[*1] M.Tech Student, Electronics & Communication, Jaypee Institute Of Information Technology, Noida, Uttar Pradesh, India

[2] Department of Electronics & Communication, Jaypee Institute of Information Technology, Noida, Uttar Pradesh, India

[3] Departments of Mathematics, Mewar University, Chittorgarh, Rajasthan, India

Sheenaagarwal26@gmail.com[1]

Abstract: Radio Frequency (RF) interference is inherent in all wireless systems and is one of the most significant design parameters of cellular and other mobile systems. In this paper, it is shown that how a non-linear adaptive Volterra filter (Polynomial filter where input and output signals are related through Volterra series) helps track the statistics of the input data and dynamics of a direct sequence spread spectrum (DSSS) system. Comparison between LMS (Least Mean Square) and RLS (Recursive Least Square) algorithms, used in filter adaptation process is shown. Results show that adaptive RLS Volterra filter based DSSS receiver is very efficient in suppressing the broadband BPSK interference.

Keywords: Broadband Interference, Non-linear filters, Adaptive filtering, Volterra series, least mean square, Recursive least square.

INTRODUCTION

While linear filters have been used widely in communication systems, many problems are inherently nonlinear and are better addressed by nonlinear solutions. Broadband interference suppression is also one of such problems [1]. Broadband interference is defined as an electromagnetic disturbance which has a bandwidth greater than that of a particular measuring apparatus, receiver or susceptible device. This is spread over the entire spectrum of the required signal; therefore it is difficult to completely remove it and thus it decreases the range over which the communication system is effective. Broadband interference usually comes from spurious radio frequency emitters. These include electric power transmission lines, electric motors, fluorescent lamps, bug zappers, etc. So in these situations the performance of linear filters is unacceptable and thus adaptive polynomial filters are used which perform satisfactorily [2]. Polynomial filters are often referred to as Volterra filters when input and output signals are related through the Volterra series expansion. Volterra filter is capable of adjusting its filter coefficients automatically to adapt the input signal via an adaptive algorithm. It works for the adaptation of signal-changing environments, spectral overlap between noise and signal, and unknown or time-varying, noise.

When interference noise is strong and its spectrum overlaps that of the desired signal, the conventional approach fails to preserve the desired signal spectrum using a traditional filter, such as a notch filter with fixed filter coefficients [3],[4]. So, here the Volterra filter plays an efficient role. In this section we will first discuss the working of Volterra filters further compare the performance of LMS and RLS algorithms so as to select the best adaptive algorithm to be used in Volterra filter for efficient broadband interference suppression and then use RLS Volterra filter for broadband interference excision from DSSS system [5], [6].

METHODOLOGY

The proposed methodology aims to suppress broadband interference from DSSS system using Volterra filter. So, for that first we understand the working of Volterra filters.

Volterra filter is governed by the Volterra series given by Vito Volterra. A filter is said to be Volterra if the filter input and output relations are given by Volterra series. The Volterra series expansion of a nonlinear system consists of non recursive series in which output signal is related to the input signal as:

$$Y(k) = \sum_{l_1}^{\infty} w_{01}(l_1)\, x(k-l_1) + \sum_{l_1}^{\infty}\sum_{l_2}^{\infty} w_{02}(l_1, l_2)\, x(k-l_1)\, x(k-l_2) + \sum_{l_1}^{\infty}\sum_{l_2}^{\infty}\sum_{l_3}^{\infty} w_{03}(l_1, l_2, l_3)\, x(k-l_1)\, x(k-l_2)\, x(k-l_3) + \text{-----------} \infty \quad (1)$$

Where, $w_{0i}(l_1,l_2,....l_i)$ for $i=0,1.....\infty$ are the coefficients of nonlinear filter model based on Volterra series and Y(k) represents the unknown system output when no measurement noise exists. $w_{0i}(l_1,l_2,....l_i)$ are functions from R^n to R. The term $w_{0i}(l_1,l_2,....l_i)$, is also known as the Volterra kernel of the system. $W_{0i}[.]$ is the n^{th} order Volterra operator. Every operator is described in the time or frequency domain with a transfer function called a Volterra kernel. Volterra kernels are calculated using Weiner Hopf equation

$$C^{MMSE}=\phi_{yy}^{-1}\,\phi_{xy}$$

Where, ϕ_{yy} is the autocorrelation matrix of the input signal ϕ_{xy} is the cross correlation vector between the desired user bit & received sequence or ϕ_{xy} can also be considered as the desired spread code [10]. From equation (1) one can think of Volterra series expansion as a Taylor series with memory. As Taylor series has no memory effect it cannot calculate distortion at high frequency as in low frequency analysis but Volterra series reveals an HD2 as high as -32 dB. This

Volterra filter characteristic is used in broadband interference detection and suppression [11], [12].

Working of Volterra filter as Broadband Interference Exciser:

In Volterra filter, the received sequence of length ‘N’ is expanded by Volterra series into a longer sequence of length ‘M’ such that M>N. It is processed with an M tap filter.

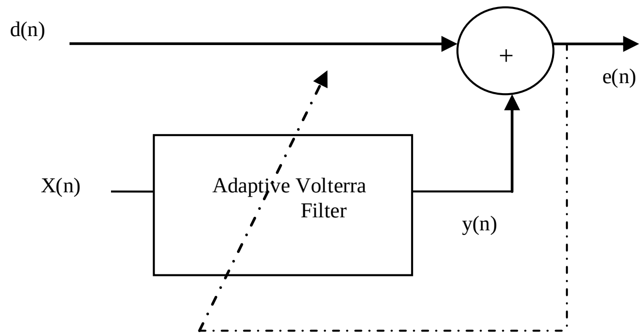

Figure.1 - A Block Diagram of Adaptive Volterra Filter

As shown in Figure 1, the system consists of two channels. The first channel is used to transmit the desired input signal s(n). However due to a noisy environment, the signal is contaminated and the channel produces a signal with the interference that is broadband in our case, so d(n)=s(n)+n(n). The second channel is left vacant and no input signal is given to it so it only captures interference x(n), which is fed to the Volterra filter. Note that the corrupting interference n(n) in the first channel is uncorrelated to the desired signal d(n), so that separation between them is possible. The interference signal x(n) from the second channel is correlated to the corrupting interference signal n(n) in the first channel, since both come from the same noise source. Similarly, the interference signal x(n) is not correlated to the desired speech signal d(n).

We assume that the corrupting interference in the first channel is linear filtered version of the second-channel interference, since it has a different physical path from the second-channel interference, and the interference source is time-varying, so that we can estimate the corrupting signal n(n) using an adaptive Volterra filter. The Volterra filter is actually a digital filter with adjustable coefficients and the LMS or RLS algorithm modifies the values of the coefficients for filtering each sample. The Volterra filter then produces an estimate of interference y(n), which will be subtracted from the corrupted signal d(n)=s(n)+n(n). When the noise estimate y(n) equals or approximates the noise n(n) in the corrupted signal, that is, y(n)≈n(n), the error signal e(n)=s(n)+n(n)-y(n)≈s(n) will approximate the clean input signal s(n). Hence, the interference is suppressed. Aim of the filter is to produce y(n) very close to d(n) or minimize e(n) such that the interference is suppressed as it reaches to the receiver [7]. According to the above idea the following performance measure used in Volterra filter is defined by Mean Square Error (MSE).

The MSE is a measure of how the algorithm converges to the true value in a mean square sense & this measurement helps us to see if our system model is indeed minimizing the error and it is sometimes called the learning curve of the algorithm [8].
Most workers have used the second and the third order Volterra filters that gives fair level of computational complexity. As for the sake of simplicity we are using second order Volterra filter [9].

Adaptive second order Volterra filter:

Volterra series expansion of second order, is described by the truncated version of equation (1).

$$Y(n)=\sum_{l_1=0}^{N} w_{01}(l_1)x(n-l_1)+\sum_{l_1=0}^{N}\sum_{l_2=0}^{N} w_{02}(l_1, l_2)x(n-l_1)x(n-l_2)$$

Where $w_{0i}(l_1,l_2)$ for i= 0, 1, . . . ,N, are the coefficients of the nonlinear filter model based on the second-order Volterra series expansion, and Y(n) represents the adaptive filter output signal. Now, the input signal X(n) is interpreted in the following way

$X(n) = [\ x(n)\ \ x(n-1)\ ---\ x(n-N)\ \ x^2(n)\ \ x(n)x(n-1)----\ x(n)x(n-N)\ \ x(n-N)x(n-N+1)\ \ x^2(n-N)]$

The filter coefficients are interpreted in the following way

$W(n)= [w_o(n)\ \ w_1(n)\ ----\ w_N(n)\ \ w_{0,0}(n)\ \ w_{0,1}(n)\ ------\ w_{0,N}(n)\ ----\ w_{N,N-1}(n)\ \ w_{N,N}(n)]$

So, the output, Y(n) is as follows

$Y(n)=W^T(n)X(n)$

Volterra kernels estimation by the LMS (least mean square) adaptive algorithm:

The well-known LMS algorithm is a sample based algorithm, which does not require collection of data and does not involve matrix inversion.

Though the LMS algorithm has its weakness such as its dependence on signal statistics, which can lead to low speed or residual errors, it is very simple to implement and well behaved compared to the faster recursive algorithms.

The Volterra filter input and output can be compactly rewritten as

$Y(n)=W^T(n)X(n)$

Where, X(n) and W(n) are N most recent inputs and their nonlinear combinations into one expanded input vector and expanded filter coefficients vector respectively.
The error signal e(n) is formed by subtracting Y(n) from the noisy response d(n)

$e(n)=d(n)-Y(n)$

For the LMS algorithm we have to minimize the error

$E[e^2(n)]=E[d(n)-Y(n)]$

The well known update equation for a first order filter is

$H(n+1)=H(n)+ \mu\,|e(n)|\,X(n)$

Where step-size(μ),controls the convergence behavior of the algorithm: the larger the value of μ the faster the algorithm converges, but this would also cause a greater misadjustment (i.e., larger residual error signal) in steady-state. For the algorithm to be stable, ' the step-size must be chosen from 0 to 2.

Volterra filter coefficients are adapted by RLS algorithm which is very robust and provides fast convergence. Signal at the receiver input consists of three components.
First one is the desired DSSS signal and is given by,

Volterra kernels estimation by the RLS (recursive least square) adaptive algorithm:

This algorithm tries to minimise the cost function:

$$J=\sum_{k=1}^{M}\lambda^{M-k}(d(n)-W^T(n))^2$$

where, 'λ' is a forgetting factor resulting in an exponentially weighted mean square error.

$$e(n)=d(n)-X^T(n)H(n-1)$$
$$k(n)=C^{-1}(n-1)X(n-1)/\lambda+X^T(n)\,C^{-1}(n-1)\,X(n)$$
$$C^{-1}(n)=\frac{1}{\lambda}\,C^{-1}(n-1)-\frac{1}{\lambda}\,k(n)X^T(n)\,C^{-1}(n-1)$$
$$W(n)=W(n-1)k(n)e(n)$$

Where, C^{-1} is the inverse of the exponentially weighted least-squares auto-correlation matrix of the input vector, P is exponentially weighted least-squares cross-correlation vector, W is the vector of coefficients, X is the input vector (containing the output of individual Volterra terms), and k is the gain vector. The equations for RLS are identical to linear RLS algorithm, with the big difference being the composition of the input vector and weighting vector.

Working of RLS Volterra filter in the broadband interference suppression from Direct Sequence Spread Spectrum System:

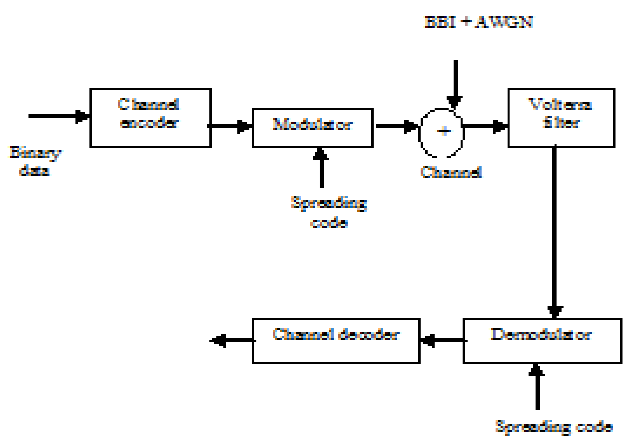

Figure.2 - Block Diagram of DSSS system along with Broadband interference introduced in the channel.

$$u(t) = U.PNS(t)d(t)\cos(w_0t)$$

where, U and w_0 mark the DSSS carrier and angular frequency, respectively, and PNS(t) is the pseudo noise sequence of chip duration T. Desired signal input power is Pu, and its effective bandwidth is Bu. Message signal is given by d(t) ϵ {+l,-1} with equal probability.

Second input signal component is the interference i(t), modeled as the broadband BPSK signal,

$$i(t) = Us.d_s(t+\tau)\cos[(w_0+2\pi f_\Omega)t+\theta]$$

Where, Us and f_Ω stands for the interference amplitude and carrier frequency offset to the BPSK carrier respectively. Random data bit delay τ and initial carrier phase θ are uniformly distributed over the [0, T) and [0,2π) interval, respectively. Interference data bit is given by $d_s(t)$ ϵ{+1,-1} having equal probability. Its power at the receiver input is Ps and its effective bandwidth is Bs.

Third component of the received signal is the additive white Gaussian noise (AWGN).

Volterra filter performance is analyzed as a function of energy per bit to noise power spectral density ratio (E_b/N_O) and bit error rate (BER).

RESULT AND DISCUSSION

Curves showing the convergence behavior of LMS and RLS algorithm:

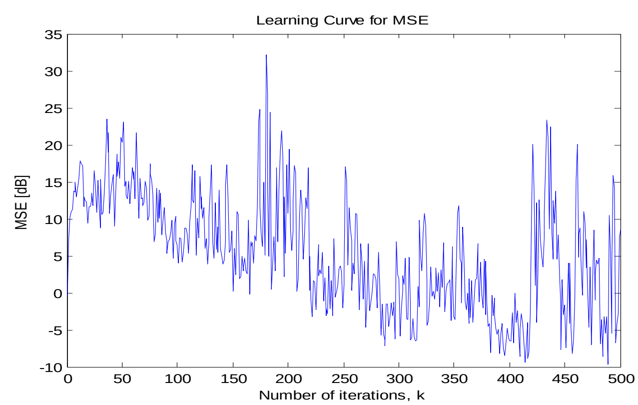

Figure.(a) The learning curve for the FIR system identification problem using LMS algorithm.

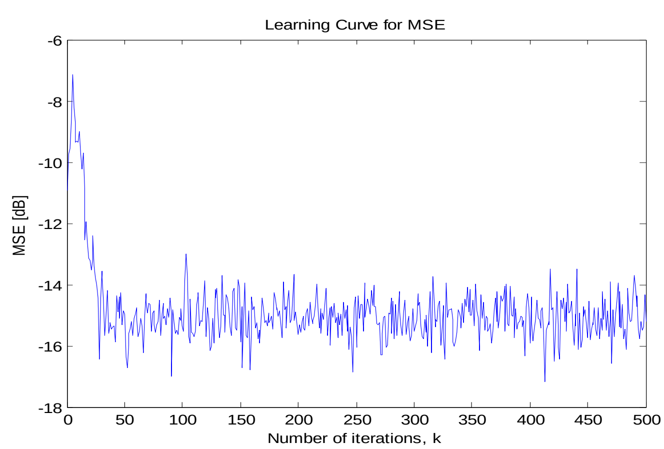

Figure.(b) The learning curve for the FIR system identification problem using RLS algorithm.

In this section, we examined both adaptive second order Volterra LMS filter (SOVLMS) and adaptive second order Volterra RLS filter (SOVRLS). As is visible from fig.(a), convergence of LMS Volterra filter is poor due to the fact that convergence factor for the LMS algorithm is bounded by the reciprocal of the product of the number of filter coefficients and input signal power. In the case of Volterra filter the terms of the filter is rarely orthogonal, since they are made up of number of inputs and products of input, same input will be present in many input terms. Because of this the LMS adaptation rate is slow for Volterra filters. The graph above shows the square error in dB versus number of iterations during the adaptation process. Simulation results shows, SOVRLS is more feasible as is visible in fig.(b) for the system identification as compared to SOVLMS. The RLS algorithm typically outperforms the LMS algorithm and is preferred method for updating the coefficients of Volterra filters.

Graph showing the broadband interference suppression after the use of Volterra filter:

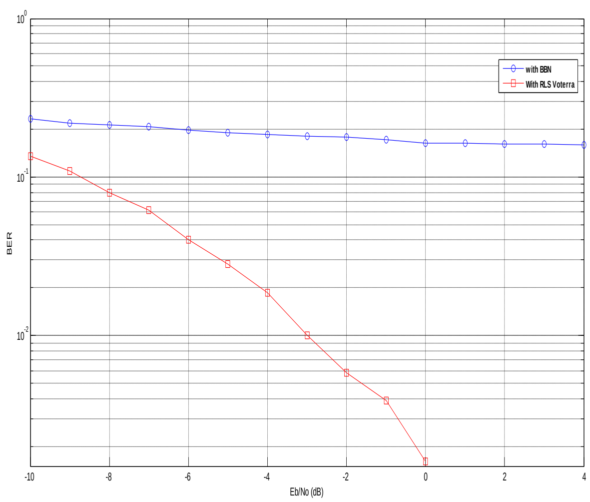

Figure.(c) Curve showing the variation of BER as a function of E_b/N_o(dB)

As the measure of Volterra filter performance in the broadband interference suppression, bit error rate (BER) is chosen. BER as a function of E_b/N_o(dB) is plotted. This simulation is done with variance $5*10^{-8}$ of AWGN noise. Spreading code length = 7; Number of input bits =1000.

Blue line in the above graph represents the BER vs. E_b/N_o(dB) in presence of broadband interference and red line shows the BER vs. E_b/N_o(dB) curve with Volterra filter. It is seen from the above fig.(c) that the DSSS receiver containing Volterra filter operate with acceptable BER even in the presence of the interference with bandwidth comparable to the desired signal.

Volterra filter provides satisfactory result in broadband interference suppression because it reduces the interference by minimizing the mean square error.

CONCLUSION

In this paper, most significant work is on a comparative evaluation of the tracking behaviors of LMS & RLS algorithm. Due to high convergence of RLS algorithm, it is much more convenient to use RLS algorithm in Volterra filter. Second most significant work is the DSSS receiver performance with the RLS Volterra filter used for the interference suppression is presented.

Interference is modeled as the broadband co-channel BPSK signal with the carrier frequency offset to the desired signal. RLS algorithms are implemented for the nonlinear filter adaptation. Results expressed in BER, show that Volterra filter is successful in the broadband interference suppression process. It enables the DSSS signal reception even in the presence of the strong broadband interference. Apart from broadband interference suppression, Volterra filters have recently gained significant interest in many advanced applications, including acoustic echo cancellation, Channel equalization, biological system modeling and image processing.

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Short Bio Data for the Author

 **Sheena Agarwal** is a 2nd year M.Tech student of Electronics & Communication department in Jaypee Institute Of Information Technology, Noida.

**Dr. R.C. Jain** is Professor & Head, ECE Department, Jaypee Institute of Information Technology, Noida, from July, 2007 to present. Ph.D, Electrical Engineering University of Alberta, Canada, 1988. M.Eng., Electrical Engineering, University of Alberta, Canada, 1985. M.E., Microwave Engineering, University of Roorkee,1978.